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EFFECTS OF GEAR CHARACTERISTICS ON THE PRESENCE OF BIGEYE TUNA (*Thunnus obesus*) IN THE CATCHES OF THE PURSE-SEINE FISHERY OF THE EASTERN PACIFIC OCEAN

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Effects of gear characteristics on the presence of bigeye tuna (*Thunnus obesus*) in the catches of the purse-seine fishery of the eastern Pacific Ocean

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Overfishing of bigeye tuna in the eastern Pacific Ocean has motivated a search for a practical means of reducing the catch of bigeye tuna in mixed species aggregations. To explore the effects of gear characteristics on the catch of bigeye tuna, a classification algorithm for the presence/absence of bigeye tuna catch in purse-seine sets on floating objects is developed, using the tree-based method, random forests. Although the location of the set was the strongest determinant of bigeye tuna catch with these data, bigeye tuna in some areas were more likely to be caught on floating objects with greater underwater depths and with deeper purse-seines. Misclassified sets that caught bigeye tuna were concentrated within certain vessels, suggesting the existence of additional vessel effects. Results indicate that fishers may avoid catching bigeye tuna in some areas by changing the depth of the material hanging from the floating object and the actual fishing depth of the purse-seine, or by moving to other fishing areas. Nonetheless, given the complexity of configuring a purse-seine, and the difficulties associated with monitoring compliance with gear regulations, fishery-wide gear restrictions would be problematic.

Keywords: bigeye tuna, fish-aggregating device, gear effects, purse-seine, random forests.

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Introduction

Concern about overfishing of bigeye tuna (*Thunnus obesus*) in the eastern Pacific Ocean (EPO) has prompted a search for practical options for reducing fishing mortality. Bigeye tuna are caught mainly by longline and in purse-seines, approximately half the catch being taken in purse-seine sets made on floating objects (IATTC, 2006a). However, the dominant tuna species in the catch of these sets is skipjack tuna (*Katsuwonus pelamis*). In contrast to the skipjack tuna population, which is estimated to be healthy (IATTC, 2006a), the most recent stock assessment for bigeye tuna indicates that fishing mortality remains too high to be sustainable (Maunder and Hoyle, 2007). Therefore, a management goal has been to find means of reducing catches of bigeye tuna in the purse-seine fishery on floating objects while minimizing losses of skipjack tuna catch. Given that operationally feasible time–area closures are unlikely to result in a sustainable bigeye tuna fishery (Harley and Suter, 2007), other options, including gear modifications, are currently being explored (Maunder, 2006).

The affects of purse-seine gear characteristics on bigeye tuna catch are of interest because of both fishery dynamics and tuna behaviour. The current purse-seine fishery on floating objects is dominated by sets on fish-aggregating devices (FADs; IATTC, 2006a). A typical FAD is a bamboo raft with old purse-seine netting hanging underneath it. Previous analyses (Harley *et al.*, 2004) have found that the floating object sets that captured the most bigeye tuna were concentrated within certain vessels. A similar result was obtained from the analysis of data from the western Pacific Ocean purse-seine fishery (Langley, 2004). At least in the EPO fishery, the specific vessels change to some extent from year to year. One possible explanation for this type of pattern is that the likelihood that a vessel will catch bigeye tuna depends on its fishing location and its current gear configuration. Gear characteristics may influence catch composition because the different species of tuna typically inhabit different depths around FADs (Schaefer and Fuller, 2002; Matsumoto *et al.*, 2007); bigeye tuna tend to be found deeper in the water column than skipjack tuna. Therefore, here we focus on gear characteristics that relate to the fishing depth of the purse-seine and the length of the material hanging below the FAD.

As a first step towards determining the feasibility of gear modifications for reducing bigeye tuna catch, we present an analysis of the presence/absence of bigeye tuna catch in purse-seine sets on floating objects from 2001 to 2005. The recent development of improved descriptive statistical techniques for large, complex datasets (e.g. Berk, 2006) makes possible an analysis of gear effects with these data. Under the assumption that it would be desirable to avoid any bigeye tuna catch, given concerns about the stock status (Maunder and Harley, 2006; Maunder and Hoyle, 2007), we studied catch presence/absence instead of catch magnitude. The tree-based method, random forests (Breiman, 2001), was used to build a classification algorithm for sets with and without bigeye tuna catch, placing emphasis on correctly predicting the presence of catch. With this analysis, we attempt to determine: (i) the relative importance of gear characteristics related to fishing depth of the purse-seine, and the length of material hanging below the FAD, on bigeye tuna catch; (ii) whether there is spatial structure in the most influential of these gear effects; and (iii) the extent to which there may exist additional vessel effects on bigeye tuna catch, beyond those described by the predictors we considered.

Data

The data used in this analysis are from purse-seine sets on floating objects collected by IATTC observers aboard large vessels (>363 t fish-carrying capacity) between 2001 and 2005. Large vessels were responsible for most of the purse-seine catch of bigeye tuna over this period (IATTC, 2006a). IATTC observers collected data on >67% of all fishing trips of large vessels between 2001 and 2005, which equates to 75% of these vessels' floating object sets (IATTC, 2006b). The IATTC on-board observer programme is described by Bayliff (2001). In each of the years 2002–2005, there was a brief (4–6 week) fishery closure between August and December (Maunder and Harley, 2006); the 2004 and 2005 closures were not observed simultaneously by all vessels.

In all, 10 421 floating object sets were available for analysis. Data were limited to sets that caught some amount of at least one of the three target species, to avoid observations for which the fish escaped capture. Repeated sets on the same floating object by the same vessel within a trip, where they could be identified, were excluded because the dynamics of fish recruitment to a floating object after a set are not well known, so it is unclear how repeat sets might differ from first sets. More than 85% of all large-vessel floating object sets between 2001 and 2005 were reported as first sets. Before analysis, the dataset was randomly divided (by year) into two parts: a training dataset with 5210 sets (2827 sets with bigeye tuna, 2383 without), and a test dataset with 5211 sets (2844 sets with bigeye tuna, 2367 without). All classification algorithms were built on the training dataset. The test dataset was used to study additional vessel effects.

To describe variability in the occurrence of bigeye tuna catch, 22 predictors were used in our analysis (see Table 1 for details). These predictors can be divided roughly into three groups: those describing aspects of fishing operations and gear, those describing the environment, and miscellaneous predictors.

Because of the differences in the vertical distribution of tuna species under FADs (Schaefer and Fuller, 2002; Matsumoto *et al*., 2007), we focus on gear characteristics that relate to the fishing depth of the purse-seine or the length of the material hanging below the floating object. The in-water depth of the purse-seine and that of the material hanging below the floating object will vary depending on a number of factors, including winds and currents. The in-water depth of the net is determined by its hanging depth and the rate at which it descends. Descent rate is a function of mesh size, dolphin safety panel use, the "hang-in" (the number of meshes per unit length along the cork line), and the weight of the purse cable and chain. In-water net depth data were not available. However, observers did record the hanging depth of the net, its mesh size, the presence or absence of a dolphin safety panel, and the time required to encircle the school of fish and purse the net. Observers also recorded an estimate of the length of material hanging below the floating object. For a FAD, this estimate is typically based on visual inspection of the FAD before it is placed in the water or after the set, if the FAD is brought on board. For floating objects occurring naturally, a visual estimate may have to be made while the object is still in the water. However, natural objects may be converted to FADs by the vessel crew, allowing the observer to see the floating object at the surface during this process.

Environmental predictors included in the analysis relate to measures of upper-ocean circulation (e.g. major currents and eddies), stratification, and productivity. Except for sea surface temperature, environmental predictors represent climatologies estimated at set locations and dates. Location and date of the set were also included as proxies for local environmental conditions not captured by the other predictors. The two miscellaneous predictors were a proxy for the non-tuna community size at the object and a proxy for the local floating object density.

The classification of each set in terms of presence/absence of bigeye tuna catch was based on the catch weights, which include discards. The frequency distribution of bigeye tuna catch per set was strongly right-skewed; the quartiles of the values were 0, 1, and 10 t, respectively, with a maximum catch of 326 t. A presence/absence variable was constructed from these data by assigning a value of 1 to every set that caught any bigeye tuna and a value of 0 to every set with no catch of bigeye tuna. In this analysis, we assume that observers' tuna species identifications are correct (but see the Discussion section below).

Methods of analysis

The ensemble method "random forests" (Breiman, 2001; Berk, 2006) was used to build a classification algorithm for the presence/absence of bigeye tuna catch. This method is a tree-based algorithm that builds on the classical Classification and Regression Tree approach (CART; Breiman *et al*., 1984). A large number of CART-like trees are constructed to form a "forest", each tree built on a different sample randomly selected from the original data. We use the random forests method because it has been demonstrated to build better classification algorithms than other methods (Breiman, 2001; Lin and Jeon, 2006), and is well suited to complex datasets with weak and/or partially correlated predictors (Berk, 2006). In addition, the estimates of misclassification errors provided by the random forests method are true forecasting errors (Breiman, 2001). The random forest procedure was implemented using the randomForest package (Liaw and Wiener, 2002) of the R statistical computing software (R Development Core Team, 2005). Forests were based on 5000 trees, and our general approach is similar to that of Lennert-Cody and Berk (2007).

In the context of this analysis, it seems reasonable to place equal, if not added, emphasis on correctly predicting the presence of bigeye tuna catch when it occurred. There are two types of mistakes that can be made: bigeye tuna catch was predicted when there was none—"false positive"; and no bigeye tuna catch was predicted when in fact there was a catch—"false negative". To understand the processes that lead to the catch of bigeye tuna, it is important to do a reasonable job of predicting the occurrence of bigeye tuna in the catch. Therefore, we consider two relative costs for the two types of mistake: equal relative costs of false negatives and false positives, and the relative cost of false negatives three times that of false positives. The relative cost ratio is a parameter that should be set by individual researchers, depending on the specifics of their particular problem (Berk, 2006).

Table 1. Predictors used to describe the presence/absence of bigeye tuna catch.

Predictor	Additional details (minimum, median, and maximum values)
Gear and operational predictors	
Vessel fish-carrying capacity (capacity)	Tonnes (397, 1 089, 2 833)
Hanging depth of the purse-seine (net depth)	Counted in strips and converted to metres (1 strip ≈ 11 m); actual fishing depth of net not measured (132, 219, 329)
Size of the mesh in the net (mesh size)	Stretch measurement in inches (3.5, 4.25, 12.0)
Dolphin safety panel (safety panel)	Presence/absence; the safety panel has a stretch mesh size of 1.25"
Maximum depth of floating object below water's surface (object depth)	Estimated in metres by the observer; actual depth of object below surface not measured (0.01, 18.1, 130)
Duration of encirclement and pursing (encirclement)	Time (decimal h) between the departure of the net skiff from the seiner and the point at which the bottom of the net was closed; this is the time during which the net reaches its maximum fishing depth (0.27, 0.52, 2.43)
Percentage of the floating object covered with fouling organisms (fouling)	Used as a proxy for the time the floating object spent in the water (i.e. soak time); the relationship between fouling and actual soak time may be compromised when vessels set upon/use objects belonging to other vessels (0, 40, 100)
Start time of the set (set time)	Local time (decimal h) of the release of the net skiff from the purse-seiner; this predictor was included because bigeye tuna may exhibit diel variability in their depth distribution when associated with floating objects (Schaefer and Fuller, 2002) (4.75, 6.68, 19.0)
Environmental predictors	
Sea surface temperature (SST)	Measured *in situ* by the observer in °C (13.0, 26.1, 31.4)
Probability of a SST front (SST)	Estimated at set locations using the NOAA National Oceanographic Data Center 4 km Advanced Very High Resolution Radiometer (AVHRR) SST data (Kilpatrick *et al.*, 2001; Casey and Evans, 2006). The locations of SST fronts were identified in daylight AVHRR images from 1985 to 2005 by the presence of bimodal distributions in local SST (Cayula and Cornillon, 1992; JJR, unpublished). For each month, the proportion of images for a pixel that contained a front and was cloud-free is the estimate of the probability of a front (0, 0.008, 0.07)
Mixed layer depth (MLD)	Metres. Monthly average by 1° area. The MLD was defined as the depth at which the temperature falls to 0.5°C below the surface temperature (data from the World Ocean Database 1998; estimates courtesy of Pacific Fisheries Environmental Laboratory, NMFS, Pacific Grove, California, as outlined in Monterey and Levitus, 1997) (0.7, 35.1, 414.0)
Depth of the seabed below the surface (bathymetry)	Metres. Sampled from the "S2004" 1-min global bathymetry database (W. Smith, 2004, unpublished; 1-min global bathymetry data), at the set location. See also Marks and Smith (2006) (−6 265, −3 935, −114)
Strong currents	Presence/absence (estimated subjectively by the observer)
Sea surface height anomaly (SSH)	Centimetres. Sampled at the set location and date from the Aviso 1/3° weekly Delayed Time Mean Sea Level Anomaly "Reference" data (DT-MSLA Ref; CLS, 2006). Anomaly estimated as the height difference from the 1993–1999 mean surface (Rio and Hernandez, 2004). The altimeter products were produced by SSALTO/DUACS and distributed by Aviso, with support from CNES (−21.25, 0.94, 34.12)
Slope of the SSH anomaly (SSH slope)	Unitless (SSH defined above) (3.8×10^{-7}, 2.3×10^{-5}, 1.5×10^{-4})
Chlorophyll *a* density (Chl *a*)	mg m^{-3}; sampled at the set location and date from monthly climatologies of chlorophyll density estimated by NASA Goddard Space Flight Center from 1998 to 2005 SeaWiFS ocean colour measurements (McClain *et al.*, 2004; Feldman and McClain, 2005) (0.06, 0.17, 2.63)
Latitude (and latitude^2)	Decimal degrees
Longitude (and longitude^2, longitude × latitude)	Decimal degrees (negative); longitude × latitude indicates the product of longitude and latitude. Higher-order terms were included to help capture spatial structure
Month	Categorical (1–12).
Year	Categorical (2001–2005).
Miscellaneous predictors	
Proxy for floating object density (object density)	The number of unique object numbers within a 5°-area around the set location and 1 month before the set date. Ideally, the number of unique objects in a given area and time window would be computed. However, this was not possible because the data do not allow objects to be tracked across vessel trips nor do the data identify objects shared with /stolen by other vessels (0, 29, 584)
Proxy for size of the non-tuna object-associated community (bycatch)	Natural logarithm of the observer's count of the number of animals (other than tuna) that were brought onto the vessel's deck dead (0, 4.29, 11.06)

We summarized the effects of predictors on the presence of bigeye tuna catch in several ways. The average percentage decrease in prediction accuracy associated with each predictor was used as a measure of its relative importance to correct classification (Liaw and Wiener, 2002). In addition, the relationships between the presence of bigeye tuna catch and the most influential of the gear predictors related to the fishing depth of the purse-seine and the underwater depth of the floating object were summarized graphically using partial dependence plots (Hastie *et al*., 2001; Liaw and Wiener, 2002). Partial dependence plots show the effect of a specific predictor on the likelihood that a set was classified as having caught bigeye tuna, taking into account the average effects of all other predictors. Partial dependence plots were also constructed within each of 40 rectangular areas (10° longitude by 2.5° latitude, between 90° and 140°W and between 12.5°S and 7.5°N) to look for spatial structure. The size of the rectangular areas and the overall region were selected according to the large-scale circulation patterns of the EPO (Kessler, 2006) and the spatial distribution of the floating object fishery (Figure 1).

As an indicator of additional vessel effects, we studied the occurrence of false negatives within vessels, because this type of error may indicate alternative fishing strategies that were successful with respect to bigeye tuna. If all vessels made the same number of sets catching bigeye tuna, the more false negatives per vessel, the greater the possibility that some aspect of the vessel's fishing behaviour might be different from that of the rest of the fleet. However, vessels did not each make the same number of sets catching bigeye tuna. Therefore, we considered the number of false negatives per vessel, taking into consideration this difference in sample size between vessels. To do this, we computed the probability that of n sets that caught bigeye tuna, there would have been r or more sets for which no bigeye tuna were predicted, using a binomial distribution. The overall binomial parameter for this calculation was taken to be the false negative rate. We refer to these probabilities as per-vessel probabilities. As there is no convincing way to assess the extent to which sets within vessels are independent, we use the per-vessel probabilities descriptively as a relative measure of vessel effects.

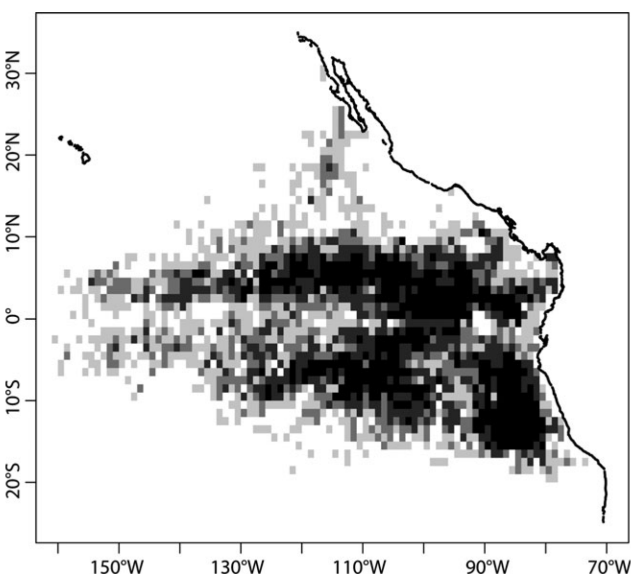

Figure 1. Number of sets on floating objects by 1° area, 2001–2005. The darker the area, the more sets (lightest grey: 1–2 sets; medium grey: 3–4 sets; dark grey: 5–9 sets; black: ≥10 sets).

Results

Both classification algorithms for the presence/absence of bigeye tuna catch had overall misclassification rates of ~17% (Table 2). At equal relative costs for the two types of error, 15% of the sets that caught bigeye tuna were predicted to have caught none (false negative), and 18% of the sets that caught no bigeye tuna were predicted to have had catch (false positive; Table 2). When emphasis was placed on the correct classification of sets with bigeye tuna (the relative cost of false negatives was three times that of false positives), the false negative rate decreased from 15% to 8%, whereas the false positive rate increased from 18% to 29% (Table 2).

Overall, the location of the set, Chl *a*, and object density were the most influential predictors in determining that a set caught bigeye tuna. However, among gear predictors that relate to the fishing depth of the purse-seine or the length of the material hanging below the floating object (Table 1), object depth had the greatest importance for predicting the presence of bigeye tuna catch with this dataset, followed by net depth (Figure 2). The same general ordering of the predictor importance was also obtained for the classifier with equal costs of false negative and false positives, and is not shown. Correlations among several predictors (Table 3) are at least partly responsible for the small values of predictor importance (Figure 2).

Sets were more likely to be classified as having caught bigeye tuna the greater the object depth (Figure 3), although this effect decreased somewhat on the deepest objects. When viewed by subarea, the greatest effect of object depth on the presence of bigeye tuna catch was between ~100°W and 130°W along the equator, and in the southern area of the fishery (Figure 4). Object depth appeared to have little effect on whether a set was classified as having caught bigeye tuna in the inshore and northernmost areas. The overall pattern was similar for net depth (not shown), with a set more likely to be classified as having caught bigeye tuna the greater the net depth, up to a net depth of ~260 m. Similar, but less pronounced, spatial structure in the effect of net depth was also evident. The influence of set location on the presence of bigeye tuna catch is also clear in Figure 4. For example, the overall magnitude of the effect of object depth in

Table 2. Number of misclassified sets and misclassification errors for (top) the classification algorithm with approximately equal relative costs of false negatives and false positives (436 vs. 438); and (bottom) the classification algorithm with the relative cost of false negatives approximately three times that of false positives (228 vs. 685).

Observed class	Predicted class		Misclassification error
	0 (no bigeye)	1 (bigeye)	
0 (no bigeye)	1 945	438	0.184
1 (bigeye)	436	2 391	0.154
0 (no bigeye)	1 698	685	0.287
1 (bigeye)	228	2 599	0.081

The term bigeye indicates sets with catch of bigeye tuna, and no bigeye indicates sets without a catch of bigeye tuna.

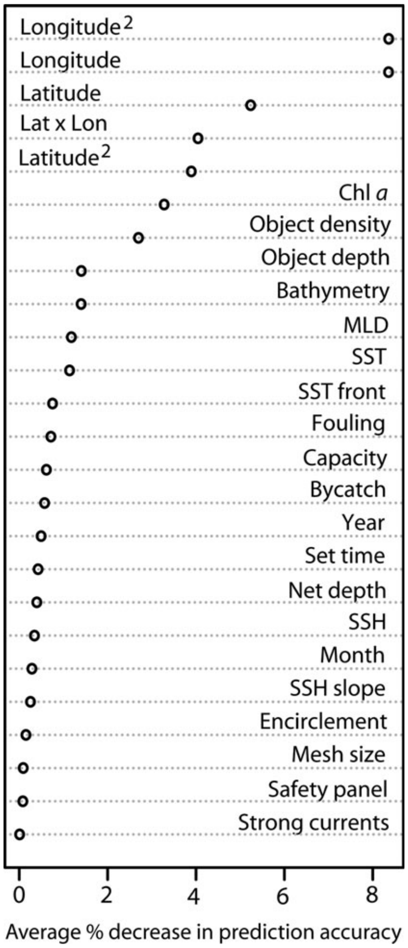

Figure 2. Predictor importance to correct classification of sets with bigeye tuna, based on the classification algorithm with three-to-one relative costs (Table 2). Predictor importance is defined as the average (over trees in the forest) of the percentage decrease in prediction accuracy and is computed on the data not included in the random samples (Liaw and Wiener, 2002). The term Lat × Lon indicates the predictor constructed by taking the product of latitude and longitude.

the inshore areas is generally less than farther offshore, regardless of latitude.

In the test dataset, there were 105 vessels over the 5-year period that made at least one set that caught bigeye tuna. The frequency distribution of per-vessel probabilities computed for these vessels using a binomial parameter of 0.08 (Table 2) is skewed, with many values close to 1.0 (Figure 5). Per-vessel probabilities at or close to 1.0 correspond to vessels with few to no false negatives among their sets that caught bigeye tuna. In other words, these were vessels whose numbers of false negatives were consistent with the false negative rate. The vessels with per-vessel probabilities $\geq$0.9 were associated with 50% of the sets catching bigeye tuna and 51% of the catch of bigeye tuna (whole dataset). In contrast, the vessels with small per-vessel probabilities are those for which the numbers of false negatives were greater than that would be anticipated at a false negative rate of 0.08. The smaller the per-vessel probability, the more unusual the number of false negatives relative to the number of sets the vessel made that caught bigeye tuna.

Discussion

We have developed a classification algorithm for the presence/absence of bigeye tuna catch in floating object sets. The presence of bigeye tuna catch could be predicted with an error of ~15% or less from information on the set location, the environment, and the fishing operations and gear (Table 2). Among the gear characteristics studied that related to the fishing depth of the purse-seine and the underwater depth of the floating object, the maximum depth of the floating object below the surface had the greatest effect on whether bigeye tuna were caught, with catches more likely on floating objects with greater lengths of material hanging below the object (Figure 3). This effect was most pronounced between ~100° and 130°W along the equator and in the southern area of the fishery (Figure 4). Nonetheless, the location of the set (latitude, longitude) was the strongest determinant in this dataset for the presence of bigeye tuna catch (Figure 2). False negatives (bigeye tuna caught but none predicted) were concentrated within certain vessels (Figure 5), suggesting that those vessels might also catch bigeye tuna in ways different from most of the fleet, i.e. in ways poorly described by the predictors included in this analysis.

One advantage of our approach for studying vessel effects is that it can be used to identify unusual observations associated with particular individuals, be they vessels, captains, or observers. In this study, per-vessel probabilities (Figure 5) provided a descriptive measure of the extent to which each vessel's sets that caught bigeye tuna were well-described by the classification algorithm. The data from those vessels associated with the smallest per-vessel probabilities might be further explored to determine if they sometimes fished differently from the rest of the fleet. Individual-set data from these vessels could be compared with fleet characteristics through the use of partial dependence plots (Figures 3 and 4) for important predictors and combinations of predictors. In addition, interviews with the captain or the crew of these vessels, or fisheries observers familiar with the vessels' activities, could be conducted to try to obtain a better understanding of how these vessels fish. More generally, per-vessel probabilities might also be used to help create categories of vessel to estimate conventional vessel effects (or skipper effects; e.g. Ruttan and Tyedmers, 2007), for instance by defining categories based on the magnitude of per-vessel probabilities.

Agreement between the results of this analysis and fisher experience is encouraging. Our results indicate that floating objects with greater lengths of material hanging below them may be more likely to lead to catches of bigeye tuna in certain areas (Figures 3 and 4), an observation consistent with the experience of fishers. Similar effects for the hanging depth of the purse-seine were also identified in this analysis (not shown), with a better chance of catching bigeye tuna in nets with greater hanging depths in the same areas. Although the effect of net depth is also consistent with fisher experience, net depth was not a particularly influential predictor in this dataset (Figure 2). This may be because net depth was correlated with several other predictors, such as longitude, Chl *a*, and vessel capacity (Table 3). Studies could be designed to allow for a separation of gear effects from environmental effects, and for a separation of different types of gear effects, two tasks which are virtually impossible with data collected during normal fishing operations. Such studies could also permit testing the effects of other operational factors, such as the length of time the floating object was adrift before the set, analyses which are difficult with data collected opportunistically.

Table 3. Spearman's rank correlation coefficient between continuous predictors described in Table 1.

	Capacity	Net depth	Mesh size	Object depth	Encirclement	Fouling	Set time	Latitude	Longitude	SST	SST front	MLD	Bathymetry	SSH	SSH slope	Chl *a*	Bycatch
Capacity																	
Net depth	0.53																
Mesh size	0.42	0.47															
Object depth	−0.02	0.09	0.01														
Encirclement	0.31	0.20	0.23	−0.08													
Fouling	0.19	0.18	0.12	0.12	0.01												
Set time	−0.06	−0.11	−0.01	−0.12	−0.05	−0.11											
Latitude	0.10	−0.03	0.05	−0.06	0.10	−0.11	−0.02										
Longitude	−0.44	−0.33	−0.19	−0.18	−0.14	−0.25	0.20	−0.39									
SST	0.22	0.12	0.14	−0.11	0.14	−0.01	0.02	0.45	−0.21								
SST front	−0.06	−0.06	−0.03	−0.02	−0.04	−0.08	0.04	−0.07	0.03	−0.24							
MLD	0.28	0.27	0.13	0.23	0.06	0.29	−0.21	0.09	−0.68	0.04	−0.14						
Bathymetry	−0.31	−0.22	−0.14	0.01	−0.08	−0.13	0.02	0.29	0.23	−0.11	−0.03	−0.16					
SSH	0.11	0.07	0.06	0.06	0.01	0.08	−0.07	0.16	−0.25	0.18	$<\lvert .01\rvert$	0.25	−0.13				
SSH slope	0.08	$<\lvert .01\rvert$	0.01	−0.05	0.05	−0.03	0.04	0.25	−0.10	0.19	−0.02	$<\lvert .01\rvert$	−0.07	0.02			
Chl *a*	−0.33	−0.30	−0.16	−0.19	−0.07	−0.32	0.16	0.05	0.63	−0.06	0.20	−0.65	0.18	−0.06	−0.05		
Bycatch	0.04	−0.01	−0.01	0.04	−0.01	$<\lvert .01\rvert$	$<\lvert .01\rvert$	0.41	−0.15	0.15	−0.07	0.12	0.14	0.13	0.08	0.02	
Object density	−0.23	−0.15	−0.11	−0.02	−0.11	−0.18	0.11	−0.28	0.59	−0.15	0.04	−0.37	0.04	−0.09	−0.08	0.43	−0.06

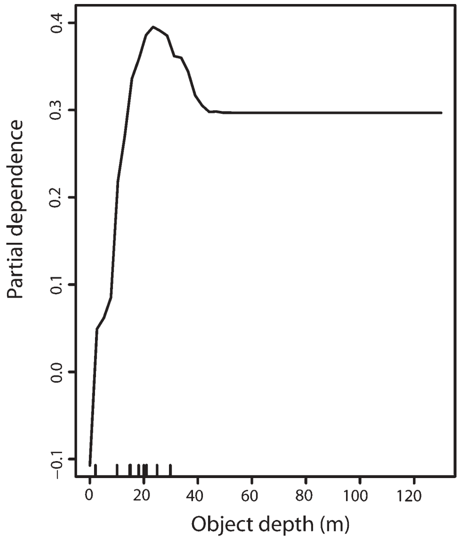

Figure 3. Partial dependence plot for object depth. The larger the value of partial dependence, the greater the chance a set would have of being classified as having caught bigeye tuna. The "rug" at the bottom of the graph shows the deciles of the values of object depth. Partial dependence is proportional to the average (over observations with a given object depth) of the logit of the proportion of trees in the forest voting for the presence of bigeye tuna (Liaw and Wiener, 2002).

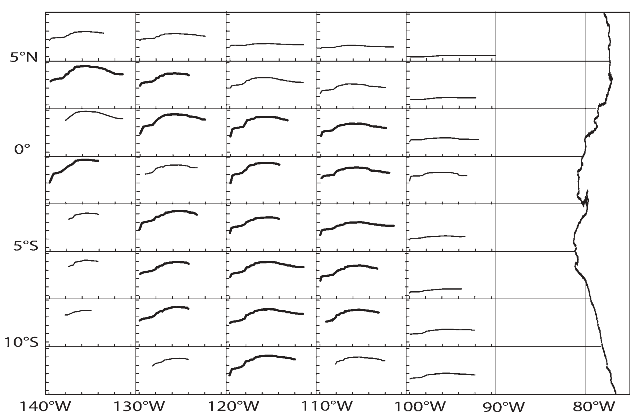

Figure 4. Partial dependence plots for object depth, by area, 90°–140°W and 12.5°S–7.5°N. For each 2.5° × 10° panel, the *x*-axis shows the object depth from 0 to 50 m by 10 m interval, and the *y*-axis shows the partial dependence from about −0.5 to 2.0 by 0.5 interval. Thick black lines indicate areas with a greater-than-average increase in the partial dependence (increase in the partial dependence was computed by rectangular area as the maximum value of the partial dependence minus the minimum value).

Specially designed studies would be necessary to quantify the details of specific gear effects and to minimize the sources of error. Here, we used observer estimates of the maximum underwater depth of material hanging below the floating object and of the hanging depth of the purse-seine, because in-water depths were not available. However, obtaining actual in-water depths would improve our ability to quantify the exact relationship

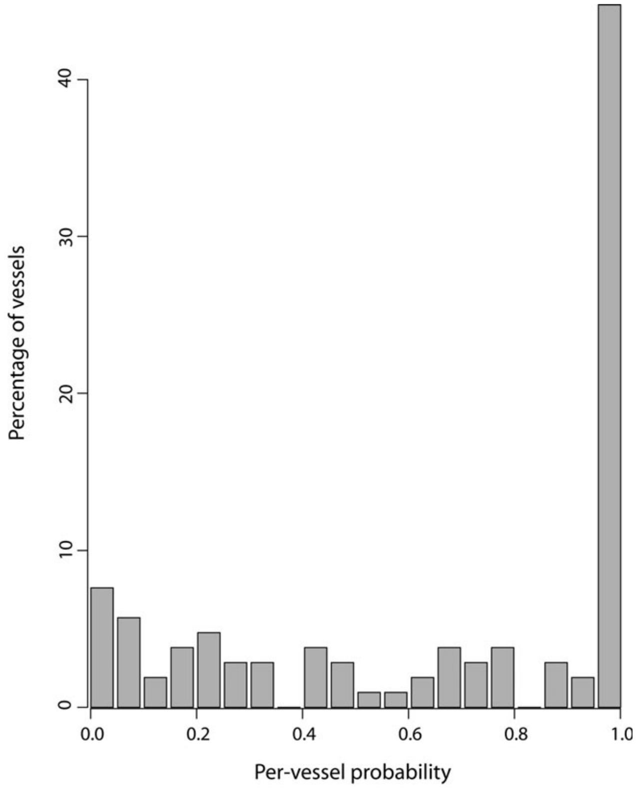

Figure 5. Frequency distribution of per-vessel probabilities. Values at or close to 1.0 correspond to vessels with relatively few to no false negatives among the sets in which they caught bigeye tuna; they are vessels whose number of false negatives are consistent with the false negative rate. Small values correspond to vessels with a larger number of false negatives, relative to the number of sets of these vessels that caught bigeye tuna.

between gear effects and bigeye tuna catches, something that would be very important if gear regulations were to be considered for this fishery. In addition, identification of bigeye tuna, particularly small fish, can be problematic. Bigeye tuna can be confused with yellowfin tuna (*Thunnus albacares*), leading to misidentification by observers. Although problems with species identification may have introduced variability into the analysis, our use of catch presence/absence as the response variable likely helped to minimize any influence on the results.

Our results suggest that the presence of bigeye tuna catch in floating object sets is a characteristic consistent with some level of fishers' control. The importance of location as a predictor indicates that the presence of bigeye tuna in the catch was not a spatially random event (Figure 2). Moreover, the importance of object depth as a predictor (Figure 2), along with the fact that the effect of object depth varied spatially (Figure 4), suggest that some degree of planning may have taken place on the part of some fishers. Most floating objects in these data were estimated to have been FADs (IATTC, 2006a), which are often assembled on board the vessel. Therefore, our results indicate that fishers may have several options available to them to try to avoid catching bigeye tuna, including changing the depth of the material hanging below the floating object, and the fishing depth of the purse-seine, in certain areas of the fishery, as well as the obvious one of changing their overall fishing location.

Given the apparent operational infeasibility of spatial-temporal closures (Harley and Suter, 2007), gear modifications might seem a reasonable option for reducing fishing mortality on bigeye tuna. Our results suggest that reducing the in-water depth of the material hanging below the floating object and the fishing depth of the purse-seine might reduce the chances of catching bigeye tuna in some areas of the fishery. However, we have considered only one target species in this analysis. Fishery-wide gear restrictions could have the undesirable side effect of reducing catches of skipjack tuna, the dominant tuna species caught in floating object sets. Moreover, many factors combine to determine the actual fishing depth of gear in a given set of environmental conditions. For example, simply setting a maximum for the hanging depth of the purse-seine might not by itself be effective at reducing the net's fishing depth. A purse-seine with a lesser hanging depth may fish deeper than one with a greater hanging depth if the weight of the purse cable and chain are increased. Therefore, regulations on a particular component, or components, of the fishing gear would not necessarily guarantee that the actual fishing depth was restricted, and monitoring compliance with gear regulations could be difficult. For these, and other reasons (Branch *et al.*, 2006), fishery-wide restrictions on the set-up of fishing gear would seem problematic.

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